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Foreclosure and Crime in Baltimore City

Beginning in 2006, the United States experienced a significant uptick in home mortgage foreclosures (Mortgage Bankers Association, 2010). The crisis, spurred by risky mortgage underwriting practices and deteriorating employment prospects (Immergluck, 2011), has wreaked havoc not just on individual homeowners and occupiers, but on entire neighborhoods (Katz et al., 2013; Harris, 2011). The situation generated concerns about the negative impact of foreclosed properties on their surroundings, and on criminal activity in particular (Katz et al., 2013; Kuebler, 2011; Wilson & Paulsen, 2008).

The primary objective of this paper is to study the causal effect of foreclosure on crime as a function of spatial proximity. The city of Baltimore is especially amenable to such an analysis. The largest city in Maryland, Baltimore is infamous for its high crime rates, with levels of property crime and violent crime that far exceed the national average (Fenton, 2014; FBI UCR Data, 2008-2014). Baltimore city has also been heavily impacted by the foreclosure crisis; it is the second hardest hit jurisdiction in Maryland. In 2009, most of Baltimore city was designated a foreclosure “hot spot” by the Department of Housing and Community Development. Moreover, even as foreclosure rates in most other parts of the country began to subside, foreclosures in Baltimore nearly tripled between 2012 and 2013. This increase represented the biggest annual gain among the twenty largest U.S. metropolitan areas, and Baltimore was one of only five cities that showed an increase in properties receiving default, auction and repossession notices, bucking a decline nationwide. (Perlberg & Dexheimer, 2013)

In this paper, I apply a fixed-effect spatial lag model to point-specific panel data on foreclosures, property crime, and violent crime in Baltimore between 2008 and 2013. I utilize a fishnet of uniform 100 x 100 meter grid cells in order to investigate the proximity effects of foreclosure data on criminal activity. The null hypothesis is that foreclosures do not impact the spatial distribution of either property crime or violent crime, while the alternative hypothesis is that higher levels of foreclosures lead to higher levels of crime in the surrounding area~~.~~

Theoretical Background

There are numerous theoretical reasons to suppose that foreclosures drive up nearby crime rates. The deterioration of foreclosed and vacant properties may signal to potential criminals that residents are less invested in their neighborhood; physical disorder may be perceived as a sign of complacency and decreased guardianship. Visible signs of decay are likely to increase as more homes become vacant. Neighborhood deterioration may also occur as homeowners facing foreclosure begin to defer maintenance on their properties (Katz et al., 2013). Meanwhile, the psychological stress that accompanies foreclosure may reduce a homeowner's capacity to remain involved in neighborhood affairs, and in turn to help maintain informal social controls within the neighborhood (Ellen et al., 2013). Social organization and informal control ("eyes on the streets") are further disrupted when residents are evicted from the neighborhood altogether (Harris, 2011; Pandit, 2011).

Routine activities theory, which assumes that criminals behave rationally, posits that offenders are drawn to accessible and desirable targets that lack adequate guardianship, reducing likelihood of criminal apprehension (Cohen and Felson, 1979). Vacant homes may also attract squatters, drug-related crimes and prostitution (Ellen et al., 2013), prompting shifts in secondary markets that feed into criminal escalation as, “more people come into contact with risky situations and by increasing the need for violent resolutions of unregulated transactions” (Arnio et al., 2012).

Concentrated foreclosures may have a disproportionate impact on crime due to nonlinearities in the effects of vacancy and turnover on the weakening of social networks and neighborhood decline. For example, if a handful of residents on the block are responsible for much of the monitoring and collective efforts, a single foreclosed property is unlikely to affect their behavior (and might even galvanize them into action). Multiple foreclosures, however, may lead residents to feel that the block is irretrievably lost and that further efforts will be futile. Moreover, if one of the key residents involved in monitoring efforts departs as a result of foreclosure (which is more likely in an environment of concentrated foreclosure), this may cause the entire social network to crumble.

Data and Methods

My overarching hypothesis is that higher levels of foreclosure lead to higher levels of crime nearby. To shed light on mechanisms, I explore whether particular types of crime – violent crimes or property crimes – are more sensitive to foreclosures. I examine point-specific foreclosure and victim-based crime data, with observations from 2008 to 2013. For the former, I utilize BNIA-JFI address-specific data for homes that entered foreclosure during the observation period. For the latter, I have compiled a comprehensive list of crimes reported in Baltimore City during that time period, combining information from the Baltimore Police Department’s Victim Based Crime Data (2011-2013) with related extracts from SpotCrime (2008-2010). Each entry is categorized as violent crime or property crime. Violent crimes include homicide, rape, robbery, and assault. Property and public order crimes include burglary, larceny, and motor vehicle theft. Total crime encompasses all reported offenses. Because property crimes occur much more frequently than violent crimes, total crime counts are highly correlated with property crime counts. Additionally, due to data irregularities, not all records could be matched to an address and subsequently geocoded; as result, approximately eight percent of reported crimes were excluded from this study.

To test the potential distance decay of the effect of foreclosures on crime, I overlay my map of yearly foreclosure and criminal activity in Baltimore with a fishnet grid made up of uniform 100 x 100 meter cells. I compare the number of crimes (in each category--property and violent) that occur within a given grid cell with the number of foreclosures that occur within the same cell, and in surrounding cells (see Appendix A)[1]. Within this framework, the annual number of crimes that occur in each grid cell is my dependent variable.

The use of small, uniform geographical units is advantageous in several respects. It addresses the modifiable areal unit problem (Openshaw, 1981), which results when aggregation to larger areal units masks underlying relationships. Research by Andresen and Malleson suggests that the underlying relationship is often stronger than suggested by measurements that rely on larger areal units of analysis (Andresen & Malleson, 2011). In this instance, assessing the spatial relationship between foreclosures and crime within larger commonly used units of analysis (e.g., MSAs, Counties, and census tracts) impose several assumptions that might hinder insight into relevant spatial processes. These popular larger units of analysis presume that the relationship between events is evenly distributed across space within relatively large areas, and that said relationship adheres to and is contained within administrative or statistical boundaries

[1] The grid cells were created in ArcGIS, by overlaying a fishnet (grid) onto ESRI shapefiles of Baltimore city. The fishnet allows various types of data to be summarized and compared using spatial joins.

that vary in shape and size. Larger spatial units also render it difficult to persuasively determine whether and to what extent distance plays a role in determining the effect of event *x* (e.g. foreclosures) on event *y* (e.g. crime). By contrast, smaller, more homogenous units of analysis (e.g., grid cells) provide more accurate means to assess the foreclosure-crime relationship, and to discern localized effects that may be a function of distance (Groff et al., 2010).

Exposure variables are often included in count models of crime to address potential variation in underlying risk of victimization. Models that predict crime counts within larger units of analysis (e.g., census tracts or counties) should take the size of the area's population into account, given the well-established link between crime volume and population size in such jurisdictions (Nolan, 2004). With small units of analysis, however, residential population is not a suitable proxy for relative victimization risk. The small size of the grid cells makes it difficult to explicitly include census-based residential population estimates or similar measures as an exposure variable. Moreover, there are many grid cells that include exclusively nonresidential areas where people may spend time, but do not live. Crime occurs in such areas even though the residential population is zero. There are also mixed-use areas where few formally reside relative to the number who may actually occupy these areas at any given point in time. For the purposes of my analysis, rather than standardizing the risk of crime by residential population, standardization of crime risk is based on physical area. The use of uniform grid cells accounts for risk of victimization by equalizing the physical area of exposure, and in turn is equivalent to including an area-based exposure variable.

I employ a fixed effects spatial lag model in order to analyze the relationship between foreclosure and crime in Baltimore city. The purpose of the fixed effects estimator is to mitigate problems associated with omitted variable bias. By holding time-invariant neighborhood characteristics constant, the model reduces the potential bias associated with heterogeneous unobserved determinants across observations that may be correlated with both crime and foreclosures. That is, it removes the influence of unobserved factors that may simultaneously affect crime and foreclosures. This in turn enables one to make stronger inferences about the relationship between foreclosures and crime. The expected number of crimes within a grid cell also depends on the other benefits and costs of committing crime (aside from those caused by foreclosure). By including fixed effects as explanatory variables, I take into account pre-existing, time invariant, location-specific contributions to the payoffs and costs of committing crime, such as geographic features, proximity to commercial areas and transit, and the distribution of building and occupancy types. In this case specifically, the suitability of the fixed effects model is confirmed by a Hausman test that yields a significant p-value.

As part of this model, I create spatial weights matrices based on first and second order queen's continuity, and then based on nearest neighbors at a variety of distances thereafter. My analysis excludes cells that contain only water. Throughout my analysis, I utilize a combination of GIS and statistical modeling programs, including ArcGIS, GRASS, Excel, and R (see Appendix B).

Results

My findings indicate a significant and positive spatial relationship between foreclosures and crime. I therefore reject the null hypothesis.

Foreclosure and crime also show significant spatial proximity. The magnitude of the relationship is greatest within the 100 x 100 meter grid cell. Specifically, one foreclosure within the 100 x 100 meter grid cell increases the incident rate of violent crimes and property crimes by

1.15 percent and 1.83 percent, respectively. That rate drops to about a 0.57 percentage increase in violent crimes and a 0.66 percentage increase in property crimes for each foreclosure within a kilometer.

The distance measures are jointly significant (χ^2 at $p<0.05$) in all models. The distance of foreclosures to property crimes is independently significant ($p<0.05$) to at least 500 meters, and marginally significant between 500 meters and one kilometer. For violent crimes, however, the distance of foreclosures ceases to be independently significant beyond 200 meters. The weakness of estimates associated with violent crimes may be to some extent a function of the relative infrequency of such crimes. Nevertheless, the empirical pattern of a distance decay effect remains apparent across all models.

Excluding cells that contain only water, on average there are about six crimes per grid cell during the observation period. The number of crimes per grid cell ranges from zero to 278, while foreclosure listings per cell range from zero to sixteen.

Both crime and foreclosures tend to cluster, exhibiting a contagion-like pattern across urban space. Estimates suggest that the influence of these clusters is significant in its own right. For grid cells that contain three or more foreclosures in a given year, the associated spike in nearby criminal activity (both property crime and violent crime) is nearly triple that of cells that contain no foreclosures. Moreover, beyond 200 meters, foreclosures have a marginally significant effect on violent crime only after there are at least two foreclosures within a cell.

Discussion and Conclusion

My results suggest that foreclosures exert a negative externality through increased crime that extends beyond their immediate surroundings; in some cases, the effect is detectable (albeit diminished) up to a kilometer away. Though the general distance effect may vary from place to place, these findings suggest that foreclosures may encourage crime beyond their immediate vicinity.

My findings come with several caveats. First, my model is underequipped to determine whether foreclosures encourage new crimes of opportunity, or instead displace crimes that would have otherwise occurred elsewhere. Thus, my results do not necessarily imply that cities reeling from the foreclosure crisis are consequently likely to experience more crime overall. Instead, my findings suggest that it might behoove police and residents to monitor affected areas more closely.

My analysis also does not tease apart the various stages of the foreclosure process; this makes it difficult to precisely estimate which aspects of foreclosure cause different types of crime. The theoretical literature suggests that vacancies play a particularly significant role in neighborhood crime levels, and it is unclear from my results whether the observed distance-decay effect on crime results from the foreclosure process overall or from vacancies specifically. Finally, my models rely on yearly foreclosure and crime counts. It is possible, however, that shorter time intervals would yield better insight into the relationship between foreclosure and crime and the processes that drive it.

My analysis prioritizes examination of foreclosure effects that decline with distance over rigorous inspection of the cumulative effects of foreclosure within an area. While some effort was made to study whether grid cells with more than one foreclosure impacted their surroundings differently, this paper does not fully and deliberately investigate the extent to which the influence of clustered foreclosures may become disproportionate once their number reaches certain thresholds. Social disorganization, broken windows, and routine activities theories, which focus on reduced informal social control and surveillance and a subsequent increase in criminal opportunity, leave ample room for such a scenario.

Even taking these caveats into consideration, my findings are strongly suggestive of a causal distance-decay effect of foreclosures on property crime and, to a lesser extent, violent crime. My results also intimate that foreclosures not only lead to elevated crime in their immediate vicinity, but also to more modest increases up to a kilometer away. The estimated effects are relatively small, and their magnitude and significance are greater for property crimes than for violent crimes. Nevertheless, these findings provide additional impetus for policy initiatives that aim to reduce foreclosures as a way of curbing the negative externalities associated with them.

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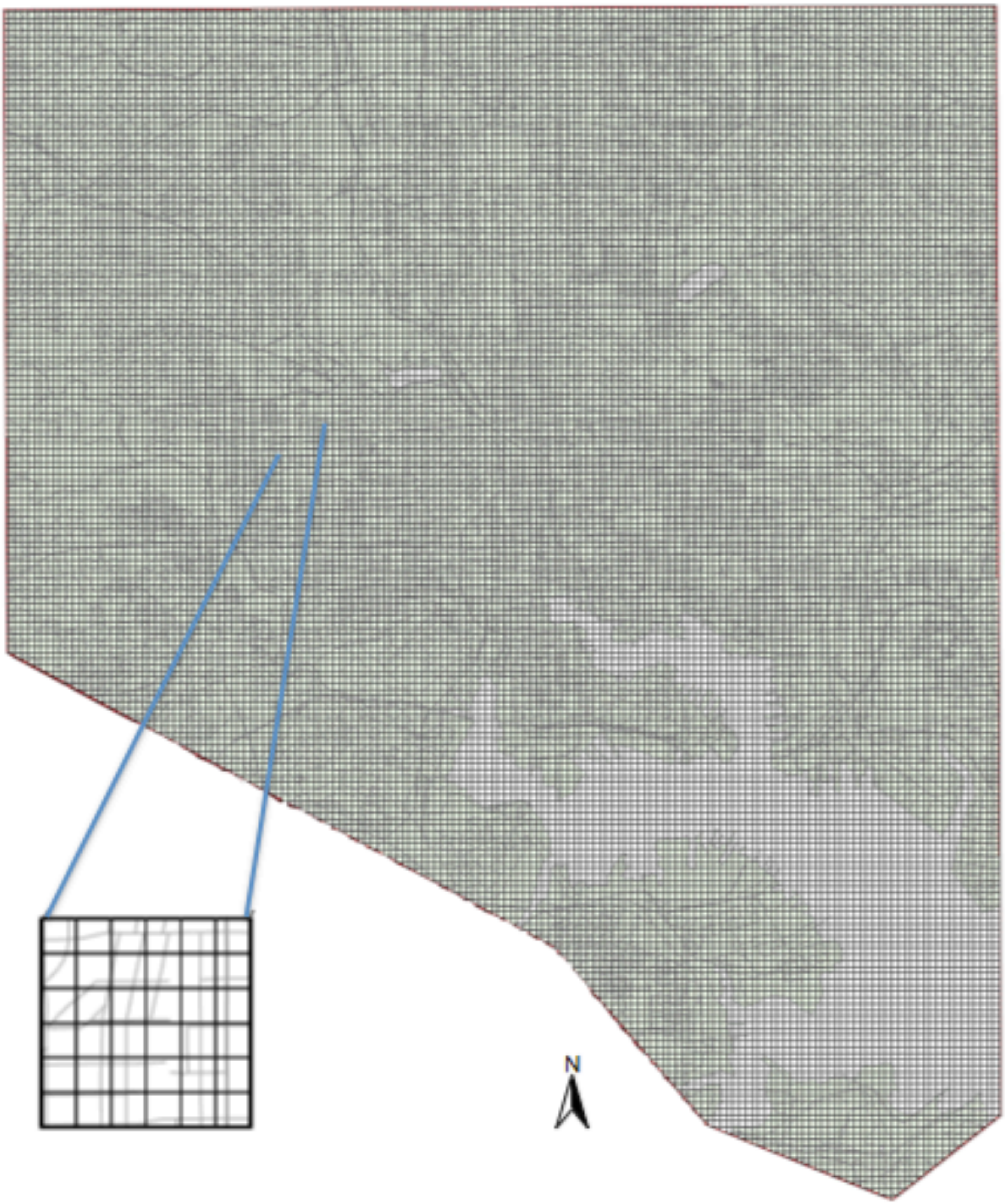
Appendix A: Units of Analysis and Study Area:
Map of Baltimore city, overlaid with 100 m x 100 m grid cells



Appendix B: R Code

```
# Load packages
library(foreign)
library(maptools)
library(network)
library(rgdal)
library(splm)
library(sp)
library(spatstat)
library(ggmap)
library(rgeos)

# Make it able to find the folder
setwd("~/Documents/school 2/Fall 2014/Applied Spatial Econometrics/Applied Spatial
Econometrics paper/Baltimoredatashapefiles")

########### Geocode foreclosure addresses ###########
# Load data file
baltf <- read.csv("baltforeclosures.csv",sep=",",header=T)
# Append city and state to address line
faddresses <- apply(as.matrix(baltf$Address), 2, function(x) paste0(x, ', Baltimore,
MD'))
# Define a function that will process Google's server responses
  getGeoDetails <- function(address){
    # Use the gecode function to query Google servers
    geo_reply = geocode(address, output='all', messaging=TRUE, override_limit=TRUE)
    # Extract desired bits from the returned list
    answer <- data.frame(lat=NA, long=NA, accuracy=NA, formatted_address=NA,
  address_type=NA, status=NA)
    answer$status <- geo_reply$status
  # If over query limit - pause for ten minutes, switch IP address, restart
    while(geo_reply$status == "OVER_QUERY_LIMIT"){
      print("OVER QUERY LIMIT - Pausing for 10 minutes:")
      time <- Sys.time()
      print(as.character(time))
      Sys.sleep(10*60)
      geo_reply = geocode(address, output='all', messaging=TRUE,
  override_limit=TRUE)
      answer$status <- geo_reply$status
    }
```

```
    # Return NA's for addresses that don't yield a match:
    if (geo_reply$status != "OK"){
      return(answer)
    }
    # Extract results from the Google server reply into a dataframe:
    answer$lat <- geo_reply$results[[1]]$geometry$location$lat
    answer$long <- geo_reply$results[[1]]$geometry$location$lng
    if (length(geo_reply$results[[1]]$types) > 0){
      answer$accuracy <- geo_reply$results[[1]]$types[[1]]
    }
    answer$address_type <- paste(geo_reply$results[[1]]$types, collapse=',')
    answer$formatted_address <- geo_reply$results[[1]]$formatted_address

    return(answer)
  }
# Initialize a dataframe to hold the results
fgeocoded <- data.frame()
# Determine where to start in address list (if script was previously interrupted):
startindex <- 1
# Load temp file
  ftempfile <- paste0('_temp_geocoded.rds')
  if (file.exists(ftempfile)){
    print("Found temp file - resuming from index:")
    fgeocoded <- readRDS(ftempfile)
    startindex <- nrow(fgeocoded)
    print(startindex)
  }
# Begin geocoding process - address by address
  for (ii in seq(startindex, length(faddresses))){
    print(paste("Working on index", ii, "of", length(faddresses)))
    # Query the Google geocoder - will pause here if over the limit
    result = getGeoDetails(faddresses[ii])
    print(result$status)
    result$index <- ii
    # Append the answer to the results file
    fgeocoded <- rbind(fgeocoded, result)
    # Save temporary results as I go
    saveRDS(fgeocoded, ftempfile)
  }
#  Add the latitude and longitude to the main data
```

```
 baltforeclosure$lat <- fgeocoded$lat
 baltforeclosure$long <- fgeocoded$lat
 baltforeclosure$accuracy <- fgeocoded$accuracy
 # Output files
 saveRDS(baltimoreforeclosure, paste0("../data/", fgeocoded.rds"))
 write.table(baltimoreforeclosure, file=paste0("../data/", infile ,"fgeocoded.csv"),
 sep=",", row.names=FALSE)

########### Geocode remaining crime addresses ###########
# Load data file
baltc <- read.csv("baltcrime08-10.csv",sep=",",header=T)
# Append city and state to address line
crimeaddresses <- apply(as.matrix(baltc$Address), 2, function(x) paste0(x, ',
Baltimore, MD'))
# Initialize a dataframe to hold the results
crimegeocoded <- data.frame()
# Determine where to start in address list (if script was previously interrupted):
startindex <- 1
 # Load temp file
    crimetempfile <- paste0('_temp_geocoded.rds')
    if (file.exists(crimetempfile)){
      print("Found temp file - resuming from index:")
      crimegeocoded <- readRDS(crimetempfile)
      startindex <- nrow(crimegeocoded)
      print(startindex)
    }
 # Begin geocoding process - address by address
    for (ii in seq(startindex, length(crimeaddresses))){
      print(paste("Working on index", ii, "of", length(crimeaddresses)))
      # Query the Google geocoder - will pause here if over the limit
      result = getGeoDetails(crimeaddresses[ii])
      print(result$status)
      result$index <- ii
      # Append the answer to the results file
      crimegeocoded <- rbind(crimegeocoded, result)
      # Save temporary results as I go
      saveRDS(crimegeocoded, crimetempfile)
    }
 #  Add the latitude and longitude to the main data
 baltcrime2008to2010$lat <- crimegeocoded$lat
 baltcrime2008to2010$long <- crimegeocoded$lat
 baltcrime2008to2010$accuracy <- crimegeocoded$accuracy
```

```
# Output files
saveRDS(baltcrime2008to2010, paste0("../data/", ,"_crimegeocoded.rds"))
write.table(baltcrime2008to2010, file=paste0("../data/","crimegeocoded.csv"),
sep=",", row.names=FALSE)

########### Convert coordinate systems ###########
# Load data files
baltcrime <- read.csv("baltcrime.csv",sep=",",header=T)
baltforeclosure <- read.csv("baltforeclosure.csv",sep=",",header=T)
# Load shapefiles
city_shp <- readOGR(dsn='Baltcity_20Line', layer='baltcity_line')
baltgrid <- readOGR(dsn='baltgrid', layer='baltgrid')

# Store original projection
origProj <- city_shp@proj4string

# Convert lat/long to Maryland grid for crime data
latlng_df2 <- baltcrime[,c('long','lat')]
latlng_spdf <- SpatialPoints(latlng_df2,  proj4string=CRS("+proj=longlat
+datum=WGS84"))
latlng_spdf <-  spTransform(latlng_spdf,origProj)
latlng_spdf_coords <- coordinates(latlng_spdf)
baltcrime$long <-  latlng_spdf_coords[,1]
baltcrime$lat <-  latlng_spdf_coords[,2]

# Convert lat/long to Maryland grid for foreclosure data
latlng_df2 <- baltforeclosure[,c('long','lat')]
latlng_spdf <- SpatialPoints(latlng_df2,  proj4string=CRS("+proj=longlat
+datum=WGS84"))
latlng_spdf <-  spTransform(latlng_spdf,origProj)
latlng_spdf_coords <- coordinates(latlng_spdf)
baltforeclosure$long <-  latlng_spdf_coords[,1]
baltforeclosure$lat <-  latlng_spdf_coords[,2]

########### Spatial weights matrix ###########
# Create a queen’s continuity spatial weight matrix
library(McSpatial)
baltqww <- makew(shpfile=baltgrid, method="queen")
baltqwmat <- baltqww$wmat

# mat2listw
library(spdep)
```

```
baltqlw <- mat2listw(baltqwmat)

# Create nearest neighbors spatial weight matrices for a variety of distances
dnn200m <- dnearneigh(coordinates(baltgrid), 0, 2000)
summary(dnn200m)
dnn500m <- dnearneigh(coordinates(baltgrid), 0, 5000)
summary(dnn500m)
dnn1km <- dnearneigh(coordinates(baltgrid), 0, 10000)
summary(dnn1km)

# mat2listw
dnn200mlw <- mat2listw(dnn200m)
dnn500mlw <- mat2listw(dnn500m)
dnn1kmlw <- mat2listw(dnn1km)

########### Define formula for a series of regressions ###########
# Rename things to make them more accessible
allcrime <- baltcrime$overallcrime_totalcount
propcrime <- baltcrime$propertycrime_totalcount
violcrime <- baltcrime$violentcrime_totalcount
foreclosure <- baltforeclosure$foreclosure_totalcount

# Define regression formulae
fmAC <- allcrime ~ foreclosure
fmPC <- propcrime ~ foreclosure
fmVC <- violcrime ~ foreclosure

########### Hausman tests ###########
# Hausman test for all crime
mod1AC<- spgm(formula = fmAC, data = baltfc, index = c("CSA2010", "Year"), listw =
baltqwmat, moments = "fullweights", model = "random", spatial.error = TRUE, lag =
TRUE)
mod2AC<- spgm(formula = fmAC, data = baltfc, index = c("CSA2010", "Year"), listw =
baltqwmat, model = "within", spatial.error = TRUE, lag = TRUE)
test2AC<-sphtest(x = mod1AC, x2 = mod2AC)
test2AC

# Hausman test for property crime
mod1PC<- spgm(formula = fmPC, data = baltfc, index = c("CSA2010", "Year"), listw =
baltqwmat, moments = "fullweights", model = "random", spatial.error = TRUE, lag =
TRUE)
mod2PC<- spgm(formula = fmPC, data = baltfc, index = c("CSA2010", "Year"), listw =
baltqwmat, model = "within", spatial.error = TRUE, lag = TRUE)
```

```
test2PC<-sphtest(x = mod1PC, x2 = mod2PC)
test2PC

# Hausman test for violent crime
mod1VC<- spgm(formula = fmVC, data = baltfc, index = c("CSA2010", "Year"), listw =
baltqwmat, moments = "fullweights", model = "random", spatial.error = TRUE, lag =
TRUE)
mod2VC<- spgm(formula = fmVC, data = baltfc, index = c("CSA2010", "Year"), listw =
baltqwmat, model = "within", spatial.error = TRUE, lag = TRUE)
test2VC<-sphtest(x = mod1VC, x2 = mod2VC)
test2VC

########### Fixed effects spatial lag models ###########
# Fixed effects spatial lag models for all crime – queen continuity
sarfemodAC <- spml(formula = fmAC, data = baltfc, index = c("CSA2010", "Year"), listw
= baltqlw, model="within", effect = "individual", method = "eigen", na.action =
na.fail, quiet = TRUE, zero.policy = NULL, tol.solve = 1e-10 )
summary(sarfemodAC)
# Fixed effects spatial lag models for all crime – more distant neighbors
sarfemodAC <- spml(formula = fmAC, data = baltfc, index = c("CSA2010", "Year"), listw
= baltqlw, model="within", effect = "individual", method = "eigen", na.action =
na.fail, quiet = TRUE, zero.policy = NULL, tol.solve = 1e-10 )
summary(sarfemodAC)

# Fixed effects spatial lag models for property crime – queen continuity
sarfemodPC <- spml(formula = fmPC, data = baltfc, index = c("CSA2010", "Year"), listw
= baltqlw, model="within", effect = "individual", method = "eigen", na.action =
na.fail, quiet = TRUE, zero.policy = NULL, tol.solve = 1e-10 )
summary(sarfemodAC)
# Fixed effects spatial lag models for property crime – more distant neighbors
sarfemodPC <- spml(formula = fmPC, data = baltfc, index = c("CSA2010", "Year"), listw
= baltqlw, model="within", effect = "individual", method = "eigen", na.action =
na.fail, quiet = TRUE, zero.policy = NULL, tol.solve = 1e-10 )
summary(sarfemodAC)

# Fixed effects spatial lag models for violent crime – queen continuity
sarfemodVC <- spml(formula = fmVC, data = baltfc, index = c("CSA2010", "Year"), listw
= baltqlw, model="within", effect = "individual", method = "eigen", na.action =
na.fail, quiet = TRUE, zero.policy = NULL, tol.solve = 1e-10 )
summary(sarfemodAC)
# Fixed effects spatial lag models for violent crime – more distant neighbors
sarfemodVC <- spml(formula = fmVC, data = baltfc, index = c("CSA2010", "Year"), listw
= baltqlw, model="within", effect = "individual", method = "eigen", na.action =
na.fail, quiet = TRUE, zero.policy = NULL, tol.solve = 1e-10 )
summary(sarfemodAC)
```